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R.F. Richards, B.N. Munk, O.A. Plumb

Washington State University, Pullman, WA, USA

W.L. Grosshandler

National Institute of Standards and Technology, Gaithersburg, MD, USA

Fire Detection and Location through Inverse Problem Solution

Abstract

A proposed method of detecting, locating, and sizing accidental fires based on the solution of an inverse heat transfer problem is described. The accuracy of the inverse problem solution algorithm, both in locating fires and determining their heat release rate is evaluated using computer synthesized fire data. The validity of the evaluation is verified using published measurements from large scale compartment fire burns.

Introduction

Inverse problem solution methods represent a suite of powerful techniques that can be applied to the problem of fire detection. The theory of inverse heat transfer problems, is quite well developed. For example, the recovery of the location and heat release rates of internal heat sources in thermally conducting solids, in radiating gases, and in convective flow situations given a limited number of discrete transient temperature measurements has been demonstrated by various workers [1].

In the present work, the heat transfer problem of interest is the convective heating of a compartment ceiling by the buoyant plume and resulting ceiling jet of hot combustion gases originating from an accidental fire. Solution of the inverse heat transfer problem involves comparing transient temperature information gathered by sensors situated at discrete locations on the ceiling to predictions of those temperatures by a numerical fire model. Minimizing the residuals between measured and predicted temperatures gives the most probable location and heat release rate of the fire which generated the plume and ceiling jet.

In the proposed system transient temperature data are assumed to be collected by n discrete temperature sensors distributed in a square grid across the ceiling of the compartment. For the proposed system few limitations on the particular method of gathering data for the inverse problem solution exist. As a result many potential sensor technologies could be candidates for an actual prototype. For example, conventional sensors such as thermocouples, or fusible links would serve well as sources of data. Newer technologies such as fiber optic sensors [2] and thermochromic liquid crystal sensors [3] now being developed promise the fire protection engineer more freedom in detection system design.

Inverse problem solution algorithm

The problem of locating a fire and determining its growth rate can be formally posed as an inverse problem. In the present study the problem is taken to be one of parameter estimation in which three unknown parameters are to be found: x, y, and α. The location of the fire is described by the Cartesian coordinates, (x,y), where the fire is assumed to lie in the plane of the compartment floor. The fire growth rate is determined by the parameter α, which follows from the functional form of the fire heat release rate assumed in the present work:

$$Q = \alpha \cdot t^2 \quad (1)$$

The quadratic form is chosen following Heskestad's recommendation [4] for the initial stages of fire growth. Here Q is the fire's convective heat release rate in kW, and t is the elapsed time from the ignition of the fire in seconds. The parameter to be found, α, is seen to have units of kW/s^2.

Solution of the inverse problem requires two steps: first prediction of the transient temperature field using a numerical fire model, and second minimization of the residuals between measured and predicted temperatures to determine the most probable location and heat release rate for the fire. The first step, determination of the temperature field given the heat source, is commonly referred to as solution of the forward problem. The second step, comparison of transient temperature data gathered by sensors to predictions of those temperatures by the numerical fire model to obtain location and heat release rate information about the fire, completes solution of the inverse problem.

In the present study the solution of the forward problem is found using the compartment fire model LAVENT. LAVENT, a two-zone fire model employing semiempirical models of the buoyant plume and ceiling jet is able to compute convective heat fluxes from a fire to the ceiling of a compartment [5]. LAVENT assumes that interactions between the plume and side wall are negligible, and that the compartment air is quiescent so that both the buoyant plume and ceiling jet remain axially symmetric about a vertical line drawn through the fire.

Forward problem solutions are found for a set of many fire scenarios, each consisting of a fire with a given location and growth rate, (x,y,α), in the relevant compartment geometry. The zone fire model LAVENT, is employed to predict the transient temperature field across the compartment ceiling for each fire scenario (x,y,α) in the set. Using the transient temperature solution for each scenario, the times at which each sensor will be activated can be determined, given both the locations of the temperature-sensitive sensors and their activation temperature. In this way, times-to-activation for a complete set of fire scenarios, that is, for all possible fire locations and growth rates, can be generated. This collection of predicted times-to-activation covering all possible fire scenarios constitutes the database of forward problem solutions used for the inverse problem solution.

In the present study a complete set of fire scenarios consisted of eight discrete growth rates from the range $0.001 < \alpha < 0.06$ kW/s^2, and 400 locations situated on a square grid at increments of 0.05D (where D is the distance between sensors) in x and y. Due to symmetry only 66 of the 400 fire locations were unique. Therefore, a complete set of forward problem solutions required a database of 528 fire scenarios. Forward problem solutions were pre-calculated and stored in RAM in the form of the locations and times-to-activation of the first five sensors to be activated by the fire: $(x_i,y_i,t_{a,i};\ i=1$ to $5)$.

Given a complete set of forward solutions, the inverse problem solution algorithm can be applied to a fire of unknown location and growth rate. The data required for the inverse problem solution are the times at which individual sensors are activated as a result of the plume of hot gases rising from the fire. Only times-to-activation for the first five sensors (n=5) activated in a given fire scenario are required. The inversion algorithm proceeds by subtracting measured times-to-activation from predicted times-to-activation and then summing the squares of the differences. The solution to the inverse problem is taken to be the values of the parameters x, y, and α for the fire scenario which minimizes the sum of squares of residuals over the complete set of fire scenarios

Simulated fire detection system

The performance of the inverse problem solution algorithm, on which the proposed fire detection system is based, was evaluated by simulating fires with known location and growth rate (x,y,α) in a compartment. Sensor times-to-activation calculated for the simulated fires were then used as data for the inversion algorithm to reconstruct the location and heat release rate of the simulated fires. To provide a statistical basis for the evaluation of the inverse algorithm, each test consisted of 1000 simulated fires, each with a randomly chosen location, and a fixed growth rate.

All simulations were run assuming a compartment 3x20x20 m in size, with a smooth, insulated ceiling. In addition, the compartment was assumed to be completely enclosed, without sources of ventilation. The temperature sensors for the detection system were assumed to be distributed on a square grid, spaced three meters apart. The activation temperature for the temperature sensors was selected to be T_a= 311 K. The sensors were assumed to hang in the hottest part of the ceiling jet, between 0 and 10 cm from the ceiling. The sensors were assumed to have negligibly small thermal mass so that their time response would be essentially instantaneous

Simulation of fire data

The fire model, LAVENT, was used to synthesize the compartment fire data required by the inverse problem solution algorithm, the sensor times-to-activation. To include the effects of uncertainty that would inevitably arise in a real system, both random and systematic errors were then added to the LAVENT synthesized fire data. Use of the same model to synthesize and then to invert data allowed the effects of these errors added to the synthesized data to be quantified.

Two types of error were added to the LAVENT synthesized data. To account for uncertainty inherent in the fire model used to produce the forward solution, a systematic error was added to the simulated sensor times-to-activation. The systematic error was assumed to be linear in elapsed time. To account for sensor measurement error, random values were also added to the simulated sensor times-to-activation. In this case, the error added was randomly chosen from a Gaussian distribution with a mean value of zero. Simulated times-to-activation, $t_{sim,i}$ were then:

$$\hat{t}_{sim,i} = \hat{t}_{LAV,i} + (a + b\hat{t}_{LAV,i}) + G(\sigma) \qquad (2)$$

where $t_{LAV,i}$ is the time-to-activation of the ith sensor as calculated by LAVENT, a and b are constants characterizing systematic error, and $G(\sigma)$ is a random number chosen from a normal distribution with standard deviation σ. Note that the parameter a has units of seconds and represents a constant time bias, while the parameter b, which is dimensionless, represents a constant percentage error in elapsed time.

To verify that the evaluation of the proposed fire detection system using synthesized compartment fire data gave realistic results, a parallel evaluation based on experimental measurements was undertaken. Measurements made during large scale test burns of wood crib fires at the Factory Mutual Research Center by Heskestad and Delichatsios [6] provided a set of realistic fire data. In that paper, measurements of ceiling jet temperatures were given versus time and radii from the fires, for eight different fires. Unfortunately, the ceiling jet temperatures reported by Heskestad and Delichatsios were given at only six radial locations. As a result, a means to 'interpolate' transient temperature data, at radial distances between those distances for which Heskestad and Delichatsios reported measurements, was employed.

The interpolation of transient temperature data from the measurements was accomplished by fitting the measurements to a correlation reported in the same work. Residuals for the data with respect to the correlation were calculated and found to fit a Gaussian distribution. Data could be generated at arbitrary radial positions by using the original correlation and then adding to the result, residuals randomly chosen from the Gaussian distribution. Temperature data generated in this way would have statistical properties identical to the original measurements.

Results

Results of the evaluation of the inverse problem solution algorithm for fire detection are given in Figs. 1 through 6. Two results are of particular interest in the present study: the speed with which the system can detect a fire, and the accuracy with which the inverse algorithm can locate and size the fire.

Figure 1 shows probability distribution functions (pdf's) for times-to-activation for the first and fifth sensors for a slow-growing fire (α=2.98 W/s^2) and a fast-growing fire (α=42.6 W/s^2). Upon activation of the fifth sensor the inversion algorithm has sufficient information to locate the fire. The slow-growing fire is seen to be located in three minutes and the fast-growing fire within one minute.

Figures 2a and b demonstrate the effect of random errors and systematic errors on the inversion algorithm's accuracy in predicting fire location. Results for both slow-growing and fast-growing fires are given. Location error is reported as the distance between predicted and actual fire locations, given in centimeters. The effect of random error is shown in Fig.2a. In that figure, where no systematic error has been added (LAVENT is assumed to be a "perfect" fire model), pdf's for simulations of fires with no random error (σ=0 sec) or moderate random error (σ=5 sec), are given. Figure 2b shows the effect of systematic or model error on the accuracy of the inversion algorithm to predict the fire location. Pdf's are given for fire data with an added random error with σ=5s for cases of systematic error corresponding to a=0s, a=40s, b=0, and b=0.6.

Errors in location predictions by the inverse problem solution algorithm are seen to be much more sensitive to random errors in fire data than to systematic errors in the fire model. This conclusion can be seen more clearly in Figs 3a and 3b where results for fast-growing fires are given. In Figs. 3a and b both the median location error and 95% confidence intervals about the median error are plotted versus random error standard deviation, σ. The 95% confidence interval represents a location error greater than the location errors for 95% or 950 out of 1000 fires in a test run. In Fig. 3a location error is plotted for three cases of systematic error: a=0, 20, 40 sec with b= 0.0 while in Fig, 3b location error is plotted for three other cases of systematic error: a=0 sec with b=0, 0.2, 0.4.

In both figures varying systematic error by varying the parameters a and b has little effect on either the median or the 95% confidence intervals for location errors. On the other hand, increasing the random error standard deviation, σ, causes monotonic increases in both the inversion algorithm's median location error and 95% confidence interval.

Figures 4a and b demonstrate the effect of random and systematic errors on the accuracy of the inversion algorithm to predict the fire heat release rate for fast and slow-growing fires. Heat release rate error is reported as the ratio of heat release rate predicted by the inversion algorithm, divided by the actual fire's heat release rate, at the time of the fifth sensor activation. The effect of random error is shown in Fig. 4a where pdf's are given for fire data with $\sigma=0$ and 5 sec with no systematic error. The effect of systematic error is shown in Fig. 4b where pdf's are given for fire data with added random error with $\sigma=5s$ and cases of systematic error corresponding to a=0s, a=40s, b=0, and b=0.6.

Figures 5 a and b show the large errors in heat release rate predictions that systematic errors in the fire model used in the inversion algorithm can lead to. Results given are for fast-growing fires only. Predicted heat release rate is seen to drop monotonically below actual heat release rate as either parameter a or b increases. Random errors can be seen to have little effect on the median heat release rate error, although larger random errors do cause the 95% confidence intervals on heat release rate error to spread substantially.

Figures 6 a and b show a comparison between evaluations based on LAVENT synthesized data and on the experimental measurements taken in a fast-growing fire as reported in reference [6]. The LAVENT synthesized data contain random error with $\sigma=5$ sec and systematic error with a=20 sec and b=0.20. The LAVENT synthesized data are seen to produce results indistinguishable from results based on measurements, if the proper random and systematic errors are applied.

Conclusions

A proposed fire detection system based on the use an inversion algorithm capable of determining the location and heat release rate of a fire has been described. An evaluation of the system under computer simulated fire conditions has produced three major results:

First, the proposed system can provide a quick response to the ignition of an accidental fire. A fast-going fire can be detected within one minute and a slow-growing fire within three minutes.

Second, the inversion algorithm shows the potential to provide accurate location and fire heat release rate information. Even with large random measurement and systematic model errors 95% of all simulated fires were located within one meter or to within one-third the sensor-to-sensor distance. Determining the size or heat release rate of a fire has been shown to be a more difficult task. With random and systematic errors of the magnitude simulated in the present study an inversion algorithm in fire detection duty could be reasonably expected to find the heat release rate of an accidental fire only to within a factor of five.

Third, the use of synthesized data in the evaluation of the proposed inverse algorithm based fire detection system has been validated. Results of the evaluation based on computer synthesized data have been shown to be similar to results based on measurements of large scale fire tests.

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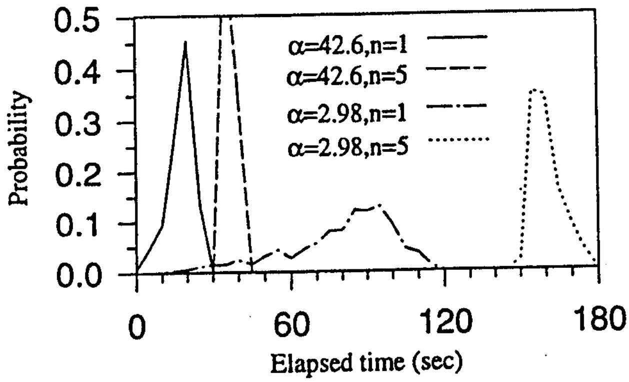

Fig. 1 PDF's for time to activation of first and fifth sensors

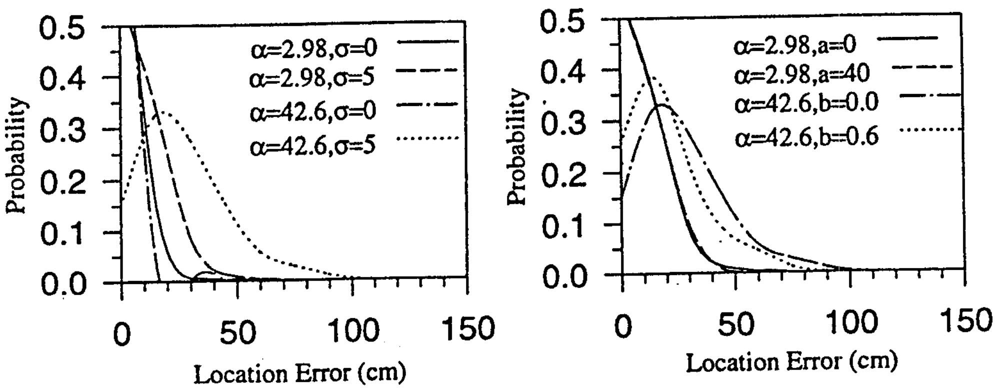

Fig. 2a,b Location error PDF's for various levels of random and systematic error. (Fig. 2a: σ = 0,5s; Fig.2b: a = 0,40s, b = 0 & a = 0s, b = 0,0.6)

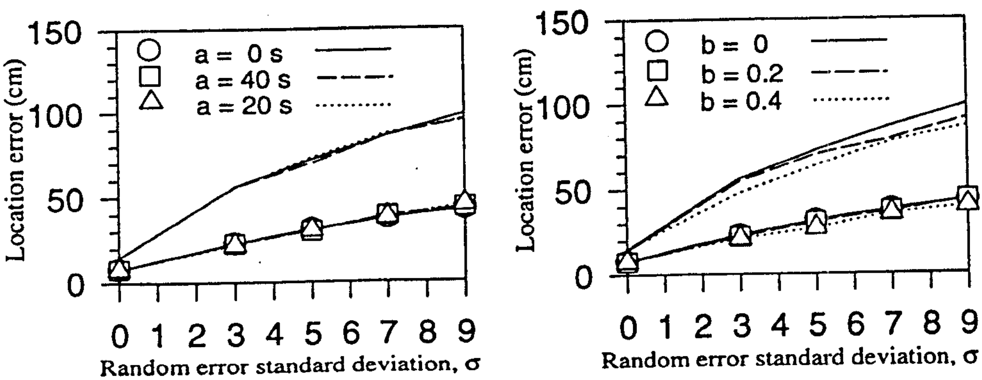

Fig. 3a,b Median location error with 95% confidence interval versus random error standard deviation, σ (Fig. 3a: a = 0,20,40s, b = 0; Fig.3b: a = 0s, b = 0,0.2,0.4).

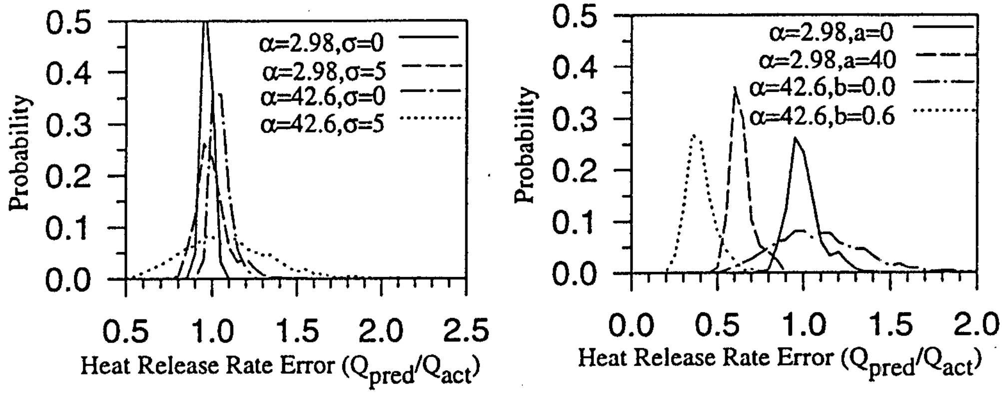

Fig. 4a,b Heat release rate error PDF's for various levels of random and systematic error. (Fig.4a: σ = 0,5s; Fig.4b:a = 0,40s;b = 0 & a = 0s; b = 0.0,0.6)

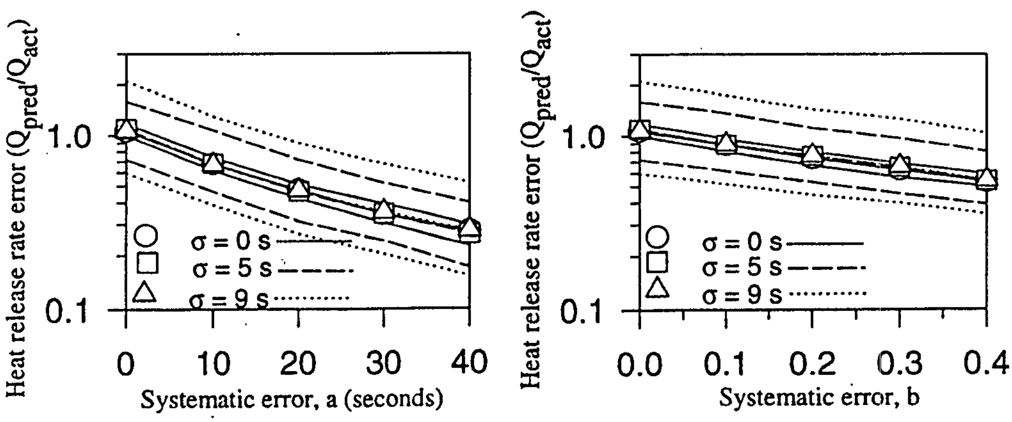

Fig. 5a,b Median heat rate error with 95% confidence intervals versus systematic error. (Fig.5a: b = 0, σ = 0,5,9s; Fig.5b: a = 0,σ = 0,5,9s).

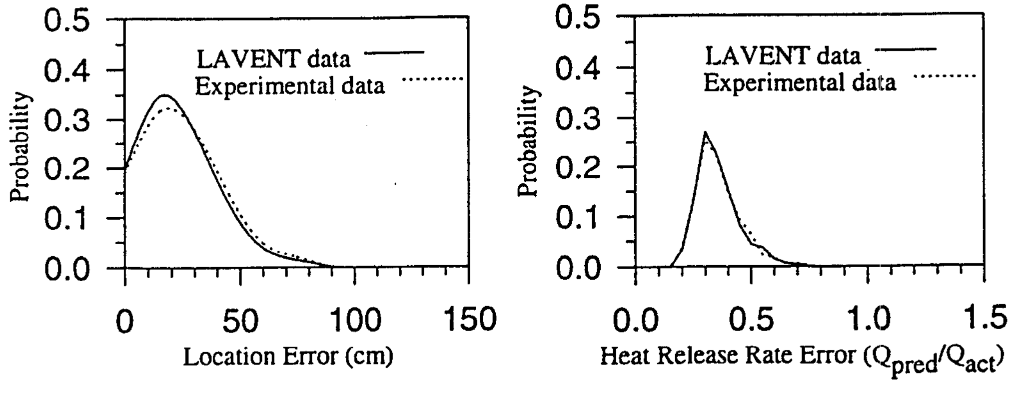

Fig. 6a,b Comparison of evaluations using LAVENT data and experimental data. (LAVENT data with random error σ = 5s, systematic error: a = 20s,b = 0.2)